Edgewood Area - Aberdeen Proving Ground, Maryland 21010-5424
U.S. Army Soldier and Biological Chemical Command

Thermal Luminescence Pattern Recognition

U.S. Patent May 20, 1997 Sheet 3 of 3 **5,631,469**

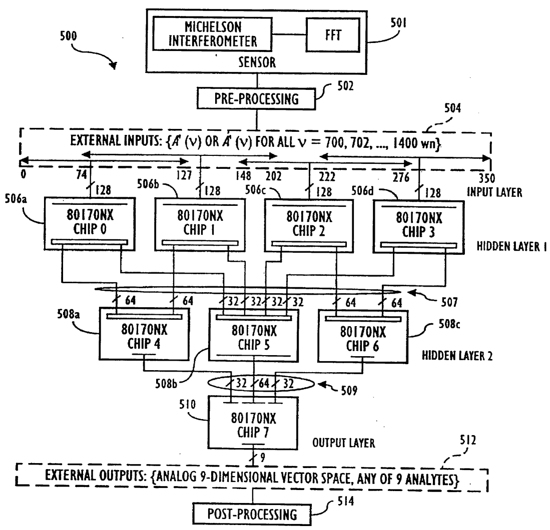

FIG. 4

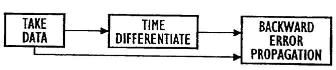

FIG. 5

This artificial Neural Network Computing (NNC) system detects surface chemical contamination via thermal luminescence (TL) spectroscopy. Features for radiometric detection of the contaminant compound (analyte), or group of compounds, are absorption and emission moieties carried in a thermal energy release by the analyte *viz a viz* energetic beam stimulation. An interferometer collects and records these stimulated emissions through digitized sets of interferograms. These data are subsequently Fourier transformed into infrared spectra and subtracted in contiguous spectral sets. The difference spectra (ΔS) are normalized, baseline-corrected, filtered for spurious electronic noise, and checked for absorption band polarity. The preprocessed ΔS is then submitted to the neural network input layer for positive or negative identification of the analyte.

Three successful TL neural network pattern recognition filters were built around an architecture design consisting of: (1) an input layer of 350 neurons, one neuron per ΔS spectral scan spanning $700 \leq \nu \leq 1400$ wavenumbers with resolution $\Delta\nu = 2$; (2) two hidden layers in 256 and 128 neuron groups, respectively, providing good network training convergence; and (3) an output layer of one neuron per analyte -- each analyte defined by a singular vector in the network training data set. The network is trained with infrared absorption spectra of chemical warfare agent and simulant compounds (or their first derivative spectra). These data sets are scaled then transformed into binary or decimal array formats for network training by a backward-error-propagation (BEP) algorithm with gradient descent paradigm. The neural network transfer function gain and learning rates are adjusted on occasion per training session so that a global minimum in final epoch training is attained. A weight matrix is generated through training of the network over many (thousands) of epochs. The final weight matrix is also referred to as the chemical detection filter, and can be transferred to eight interconnected INTEL 80170NX Electronically Trainable Analog Neural Network (ETANN) chips housed and interconnected on a mother circuit board. These neural network pattern recognition systems are integrated into a mobile prototype thermal luminescence field sensor (TLS) for the in situ spectral discrimination of heated organic liquid layers on the ground and evaporated vapor caused by beam irradiation.

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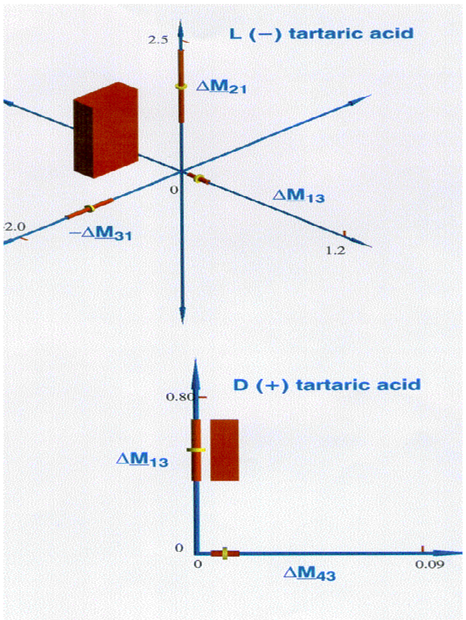
Mueller Matrix Pattern Recognition

Artificial neural network systems were built for detecting chemical and biological material (CBM) by pattern recognition of their polarized light scattering signatures. Backward-error propagation and adaptive gradient descent methods perform network training. Data measured via a differential-absorption Mueller matrix sensor (DIAMMS) comprise *domains* that uniquely represent the CBM material in backscattering of pulsating and polarization (phase) modulating wavelength-paired infrared laser beams. These *domains* are configured from those differential Mueller elements that abruptly change as the laser beam switches on and off an IR absorption band of the CBM. They are generally a minor subset of the full 16-element Mueller matrix field, per pair of irradiating CO_2 laser beams.



The figure on the left illustrates domains in Mueller matrix space for stereoisomers of tartaric acid, i.e., differential element data $\Delta\underline{M}_{ij} = \underline{M}_{ij}(\lambda_r, \alpha) - \underline{M}_{ij}(\lambda_o, \alpha)$, where ij is {21, 31, 13, 43}, λ_r and λ_o are resonance and reference (non resonance) laser beam wavelengths, respectively, and α is backscattering angle. These experimental values of $\Delta\underline{M}_{ij}$ are selected from the complete field of 15 normalized elements of the Mueller matrix that are statistically disjoint. They are disjoint in the sense that there is no overlap between sets from their average value ± one standard (SD) deviation; $\underline{M}_{ij}(\lambda_r, \alpha) \cap \underline{M}_{ij}(\lambda_o, \alpha) = \varnothing$, from a range of beam orientations $\alpha = 90.00^0 \pm 20.00^0$ in 0.01^0 increments (i.e., 4000 measured elements per set).

The neural network architecture designed for the DIAMMS is comprised of an input layer of 15 nodes comprising $\Delta\underline{M}_{ij}$ elements (e.g., see the above figure) and correlation coefficient between $\{M_{ij}(\alpha, \lambda_r)\}$ and $\{M_{ij}(\alpha, \lambda_0)\}$, a fully connected hidden-layer with 200 nodes, and an output layer of 4 nodes where each CBM is assigned a unique binary 4-vector. The network weight matrix, a final product of network training and learning, associates the network output 4-vector to chemical/biological identity. A backward-error propagation algorithm with gradient descent paradigm is used in the network training/learning phase, as is a genetic algorithm that measures the contribution each input variable makes in developing the network weight matrix. (Those input variables contributing little to the weight matrix could be disconnected from the network architecture, thus simplifying architecture structure without degrading network performance.) A successful mapping of incoming sensor data by the trained network weight matrix onto a CBM's Mueller matrix space will trigger a detection alarm event.

References:

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